Evaluation of Spatial Interpolation Methods for Wind Speed and Direction: A Case Study in Split-Dalmatia County

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Abstract

Wind speed and direction are spatial variables that vary over both time and space. These variables are crucial for urban and spatial planning, agriculture and crop management, sports activity planning, aerial navigation, air pollution modeling and fire management. This paper investigates the effectiveness of several interpolation methods for predicting wind speed and direction at unknown locations, using measurements from a network of weather stations. Four well-established methods were considered: Natural Neighbor, Inverse Distance Weighting (IDW), Kriging, and Ordinary Kriging.

Data were collected from 28 weather stations distributed across Split and Dalmatia County. In two experiments, the four unknown stations were chosen to represent: 1) a station spatially surrounded by known measurements, and 2) stations representing typical geographical challenges, such as land, coast, canyon, and island locations. For each experiment, scenario, and interpolation method, we calculated and analyzed the Root Mean Squared Error (RMSE), Mean Absolute Error in the u-direction (MAE u), and Mean Absolute Error in the v-direction (MAE v). The analysis revealed that the highest errors occurred during Bora wind conditions. Among the methods, Ordinary Kriging demonstrated the lowest prediction error.

1. Introduction

Having timely and accurate wind spatial distribution is important in many applications, such as wind energy generation, urban planing and environmental monitoring. Wind is a natural movement of air caused by variations in air pressure due to the uneven heating of the Earth. Wind is usually measured using anemometers taken at a height of 10 meters above the ground to standardize data collection and described with wind speed and wind direction. However, wind measurements typically reflect the wind conditions at the specific location where they are taken, but they may not accurately represent the wind in surrounding areas. Thus methods for spatial interpolation and flow modeling are utilized for predicting wind parameters in the surrounding areas. Accurately determining of wind speed and direction is challenging due to the limited availability of measured data, which is typically collected at specific locations such as airports, meteorological institutes, and dedicated monitoring stations. However, the need for precise wind data extends beyond these locations, particularly in remote areas where such measurements are crucial for various applications. Performance and accuracy of spacial interpolation methods used for wind speed and direction estimation is often limited by the number and distribution of known measurement. With advancements in technology, high-quality weather stations have become more affordable, enabling widespread deployment by individuals and organizations. Companies providing weather stations also contribute to open-access meteorological databases, offering real-time and historical wind data. In general , access to larger number of wind measurement increases the accuracy but also increases the price of installation and maintenance. Placement of these weather stations plays the crucial role in determining the wind over the entire region. Due to topographic features, uneven or sparse distributions can lead to significant errors and interpolation accuracy can be exacerbated by the topographical features of the study area.

Moreover, it is essential to assess the variability of interpolation accuracy across different conditions, including seasonal variations, wind types, and times of the day. Understanding these factors helps determine the extent of interpolation errors and whether certain scenarios yield more precise results.

This paper describes the methodology and results of systematic evaluation of four main spatial interpolation methods - Kriging, Ordinary Kriging, Inverse Distance Weighting (IDW), and Natural Neighbors for wind speed and direction estimation on a study area of Split and Dalmatia County . We utilize ground truth data from weather stations available via Weather Underground (Weather Underground, n.d.), focusing on the Split-Dalmatian County, a region characterized by diverse terrain, including islands, coastal areas, urban environments, canyons, and remote countryside. By analyzing wind data from various landscapes, we aim to evaluate the effectiveness of interpolation methods in different geographic contexts and determine the associated error margins when comparing interpolated values to known ground truth measurements.

2. Related Work

Due to sparse distribution of official weather stations worldwide and inability to access the wind data at specific location, many applications employ some kind of spatial interpolation methods. Wind speed and direction interpolation is a crucial task in meteorology, wildfire spread modeling, renewable energy planning, and environmental modeling. Several studies have explored different interpolation techniques and their effectiveness in estimating wind parameters across diverse geographic regions. Wind Interpolation is a process used to estimate wind speed and direction at locations where no direct measurements are available. The most commonly used techniques include:

- **Kriging and Ordinary Kriging** – Kriging methods are geostatistical interpolation techniques that consider both spatial autocorrelation and measurement location distances (Keskin and Ozdogu, 2011). Ordinary Kriging (OK) is frequently applied for wind field estimation due to its ability to provide unbiased predictions with minimal variance (Nynke Hofstra, 2008).

- **Inverse Distance Weighting (IDW)** – IDW assumes that nearby points have more influence on the interpolated values than distant points (Keskin and Ozdogu, 2011). While computationally efficient, IDW can struggle in areas with complex wind dynamics.

- **Natural Neighbor Interpolation** – This method provides smooth and continuous surface estimation while preserving the integrity of known values (Nynke Hofstra, 2008). However, its performance depends on data density.

- **Spline Interpolation** – Spline methods create a smooth surface by fitting piecewise polynomials between known data points (Pratik Nag, 2023). They are useful for capturing gradual wind variations but may introduce unrealistic oscillations in sparse datasets.

- **Machine Learning and Hybrid Methods** – Recent studies have introduced hybrid approaches, such as combining Kriging with neural networks or deep learning techniques like Bivariate DeepKriging (Pratik Nag, 2023), which improve prediction accuracy in complex terrains.

Despite advancements in interpolation techniques, accurately predicting wind speed and direction remains a significant challenge. One of the primary difficulties stems from data sparsity, as wind measurement stations are often unevenly distributed, leading to large gaps in spatial data. This issue is particularly pronounced in remote regions such as islands and mountainous areas (Keskin and Ozdogu, 2011). Additionally, anisotropy in wind fields poses another major challenge, as wind patterns exhibit strong directional dependence influenced by geographical features like coastlines, mountain ranges, and urban structures. Traditional interpolation methods often struggle to capture these complexities (Nynke Hofstra, 2008). Furthermore, the inherent temporal variability of wind characteristics complicates interpolation efforts, as wind conditions can change rapidly over time, making static datasets insufficient for precise predictions (Pratik Nag, 2023).

Beyond these primary concerns, several secondary challenges further impact the accuracy of wind interpolation. Computational complexity is a notable issue, as advanced methods such as Kriging and machine learning-based interpolation demand substantial computational resources, especially when working with large datasets (Pratik Nag, 2023). Moreover, error propagation from measurement inaccuracies in weather stations can degrade the reliability of interpolation models (Nynke Hofstra, 2008). Finally, seasonal and diurnal variability introduces additional uncertainty, as interpolation performance may fluctuate depending on seasonal cycles, time of day, and specific wind regimes. This is particularly relevant in regions like Split-Dalmatia, where characteristic winds such as Bura, Jugo, and Maestral exhibit distinct behaviors (Nynke Hofstra, 2008).

While these challenges have been widely recognized in the literature, there has been limited research on the performance of interpolation algorithms in complex and large-scale environments. This paper seeks to answer the research question: *How does the accuracy of major interpolation methods vary with different placements of test locations?*. Our approach involves a systematic evaluation of interpolation algorithms using a network of weather stations as ground truth data. By varying wind type, season, and time of day, we assess how these factors influence interpolation accuracy. The results are obtained by comparing interpolation errors against measured data at designated test locations, providing valuable insights into the reliability of different methods under diverse conditions.

3. Materials and Methods

3.1 Study Area

The study area selected for this research is Split-Dalmatia County, a diverse region in southern Croatia that encompasses coastal zones, islands, urban centers, and inland mountainous areas. Due to its complex geography and dynamic meteorological conditions, this region presents a unique challenge for wind speed and direction interpolation. The presence of the Adriatic Sea, coupled with rugged terrain, creates highly variable wind patterns influenced by both large-scale atmospheric processes and local topographic effects.

Split-Dalmatia County, figure 1 spans approximately 4,524 km², making it the largest county in Croatia by land area. It includes key cities such as Split, Trogir, Makarska, and Sinj, along with numerous islands (Brač, Hvar, Vis, Šolta, and others). The region's climate is predominantly Mediterranean along the coast, characterized by mild winters and hot, dry summers, whereas the inland areas exhibit a more continental climate, with colder winters and higher annual precipitation.

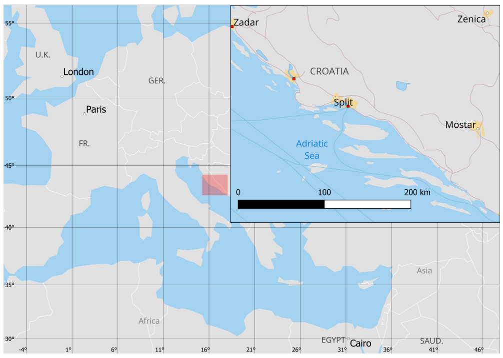

Figure 1. Geographical Location of the Study Area.

These wind systems exhibit significant seasonal and diurnal variations, making accurate interpolation of wind speed and direction highly dependent on local geography and measurement density.

The topography of Split-Dalmatia County plays a crucial role in wind flow dynamics. The presence of mountain ranges (Biokovo, Mosor, Dinara), deep valleys, and numerous islands creates microclimates that influence wind variability. Orographic effects such as valley channeling, mountain waves, and coastal breezes introduce additional complexity to wind interpolation.

Coastal areas, particularly near Split and Makarska, experience strong sea-land breeze circulations, while mountainous and inland areas exhibit gap winds and downslope accelerations. These factors make standard interpolation methods, such as Kriging and IDW, prone to inaccuracies if terrain effects are not adequately accounted for.

3.1.1 Data Collection and Meteorological Stations

To analyze wind interpolation accuracy, this study utilizes ground truth data from meteorological stations distributed across Split-Dalmatia County. Weather Underground (WU) Network (Weather Underground, n.d.)– A publicly accessible network of personal and official weather stations providing real-time and historical wind data.

The station density varies significantly across the county, with higher concentrations in urban areas and along the coastline, while rural inland areas suffer from lower observational coverage. This **non-uniform distribution** poses challenges for wind interpolation, as interpolation accuracy is highly sensitive to station density and spatial arrangement. All maps and spatial data in this study are represented using the WGS 84 coordinate system (EPSG:4326).

3.2 Data Collection

This study utilizes publicly available meteorological data from the Weather Underground network, focusing on weather stations distributed across Split-Dalmatia County. There are approximately 52 weather stations in this region, with a denser concentration near the coastline and urban centers, while inland and rural areas exhibit a lower station density.

To ensure temporal representativeness, historical weather data was collected over a one-year period, spanning nine randomly selected days per month. Given that most weather stations log data at five-minute intervals, this results in 288 daily records per station. With data aggregated from 52 stations, the dataset comprises approximately 1.5 million wind records per year.

Raw data collected from individual stations is initially unsorted and thus requires preprocessing before it can be used for wind interpolation analysis. The primary challenge is ensuring that data from all stations is synchronized to represent the same timestamps, as interpolating wind speed and direction across the region is only meaningful if measurements are taken at the same moment.

To address this, the dataset is first **grouped by timestamp**. Given that some weather stations report data at different intervals (e.g., 5-minute, 15-minute, or 30-minute intervals), timestamps with insufficient station coverage are discarded. Specifically, timestamps where fewer than 30 stations report data are excluded to ensure reliable interpolation results.

To ensure consistency across seasonal variations, the dataset is refined so that each timestamp includes measurements from the same subset of weather stations. This prevents situations where, for example, summer data is recorded from one group of stations while winter data comes from an entirely different set. After applying this filtering process, only timestamps where a selected 28 stations have continuously recorded data throughout the year are retained.

The exclusion of other weather stations is primarily due to three factors. Some stations were installed within the past year and lack a complete historical dataset, making them unsuitable for long-term analysis. Others experienced hardware or connectivity failures, such as network outages, sensor malfunctions, or maintenance downtime, leading to missing data. Additionally, certain stations exhibited data inconsistencies, intermittently failing to record or store historical data, which could compromise the reliability of the dataset. By addressing these issues, the dataset remains robust and suitable for evaluating seasonal trends in wind patterns.

3.2.1 Scenario-Based Data Segmentation

Once the dataset is synchronized, it is further categorized into predefined wind scenarios to enable a finer analysis of wind behavior under different conditions. The classification process is based on three key meteorological factors: wind type, season, and time of day.

Wind Type Classification Wind direction is categorized into three primary wind types based on prevailing wind patterns in the region, as shown in Table 1.

Wind Type	Direction
Bura (Bora)	N, NE, NNE
Jugo (Sirocco)	S, SE, SSE
Maestral	NW, WNW, WSW

Table 1. Wind type classification.

A timestamp is classified under a specific wind type if at least 35% of stations report wind blowing from a corresponding direction. Timestamps where wind direction is highly variable are excluded from analysis.

Seasonal Classification Table 2 defines the meteorological seasons used to segment the wind data for interpolation analysis.

Season	Period
Winter	December 21 – March 19
Spring	March 20 – June 20
Summer	June 21 – September 22
Autumn	September 23 – December 20

Table 2. Seasonal classification.

This classification ensures that wind interpolation accuracy can be assessed across different climatic conditions.

Time-of-Day Classification Table 3 presents the four daily time intervals used to group wind measurements based on the time of day. This segmentation allows for the evaluation of diurnal wind variations and their impact on interpolation accuracy.

Time Interval	Hours
Morning	06:00 – 11:59
Midday	12:00 – 17:59
Evening	18:00 – 23:59
Night	00:00 – 05:59

Table 3. Time-of-day classification.

3.2.2 Final Scenario Composition

Theoretically, this classification system results in 48 distinct wind scenarios (*3 wind types* × *4 seasons* × *4 time periods*). However, due to natural wind pattern variations and the limitations of the dataset, certain scenarios are underrepresented or absent. For example, Maestral winds are rarely observed in winter, and some wind directions are too inconsistent to be classified definitively, leading to their exclusion.

Additionally, a portion of the dataset is discarded due to the inherent difficulty of accurately classifying wind direction in cases where measurements are ambiguous or fluctuating. Ultimately, the dataset contains 28 validated wind scenarios, which form the basis for further interpolation analysis.

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3.3 Methodology

This section outlines the methodology used for wind speed and direction interpolation. We apply four commonly used spatial interpolation methods and strategically designate a subset of weather stations as unknown and compare the interpolated results with the actual measurements.

Interpolation techniques are essential for estimating wind conditions at unmeasured locations based on known observational data. The four interpolation methods used in this study have been widely employed in meteorology and geostatistics:

- **Kriging with Covariance Adjustment** – A geostatistical interpolation method that estimates values at unknown locations by modeling spatial autocorrelation. Originally introduced by Krige (Krige, 1951) and formalized by Matheron (Matheron, 1963), Kriging is widely used in wind data interpolation. In this study, we modify the covariance function to incorporate surface roughness index, temperature, and pressure, recognizing that these factors influence wind behavior. The adjusted covariance function is given as:

$$C'(h) = \sigma^2 (1 - \gamma(h)) \cdot f(R, T, P) \tag{1}$$

  where:

  - $f(R, T, P)$ is a correction factor adjusting covariance based on local terrain roughness (R), temperature (T), and pressure (P),
  - R represents the surface roughness index, accounting for differences in terrain,
  - T and P are the temperature and pressure values at the unknown location, influencing wind behavior.

  Since we are designating known stations as unknown, we have access to their temperature and pressure data, allowing us to refine Kriging interpolation with this additional information.

- **Ordinary Kriging** – A variant of Kriging that assumes a constant but unknown mean across the study area, making it suitable for wind data interpolation (Journel and Huijbregts, 1978).
- **Inverse Distance Weighting (IDW)** – A deterministic interpolation method where values are estimated as a weighted average of nearby observations, with weights inversely proportional to distance (Shepard, 1968). This method assumes that closer stations have a stronger influence on the interpolated values.
- **Natural Neighbors** – An interpolation technique that determines values by assigning weights to the nearest observed points using Voronoi tessellations (Sibson, 1981). It is well-suited for irregularly spaced data.

3.3.1 Experimental Setup and Use Cases To evaluate the performance of these interpolation methods, we utilize data from 28 weather stations in Split-Dalmatia County. In each interpolation scenario, we designate 4 weather stations as unknown, using their true recorded values for validation, while the remaining 24 stations serve as known input data.

The interpolation is performed under two distinct conditions:

1. **Scenario 1: Typical Locations** – The unknown weather stations are selected to represent diverse geographical environments. The location of the selected unknown stations as shown in figure 2. These stations are located at locations representing:Countryside – Open, rural areas with minimal obstacles to wind flow, Island – A coastal station influenced by sea-land breeze interactions, Canyon – A location with complex wind behavior due to topographical constraints and Boulevard in a Mildly Urban City – A semi-urban setting where built structures partially affect wind patterns.
2. **Scenario 2: High-Density Areas** – The unknown weather stations are positioned within or near clusters of known stations. This setup examines interpolation accuracy in areas with relatively high measurement density. These stations are shown in figure 3.

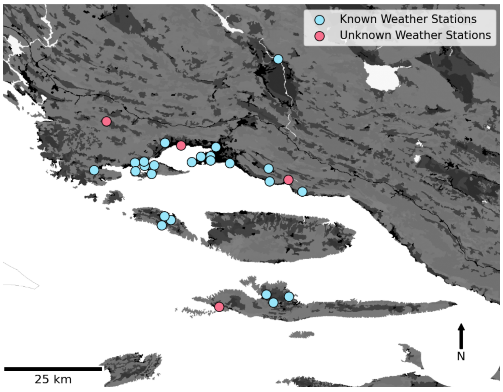

Figure 2. Unknown weather stations – typical locations.

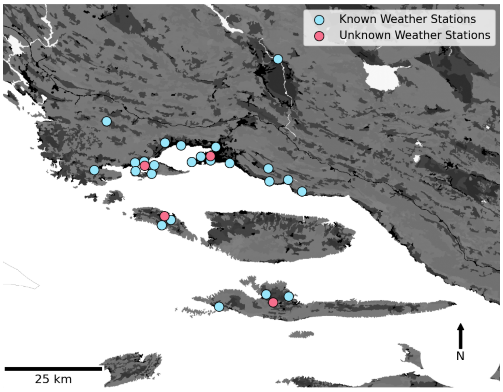

Figure 3. Unknown weather stations – high-density areas.

Both scenarios are tested across 28 wind data scenarios, which classify wind behavior based on wind type, season, and time of day.

3.3.2 Error Measurement Metrics To quantitatively assess interpolation accuracy, we employ the following error metrics:

Root Mean Square Error (RMSE) RMSE is used to measure the overall interpolation accuracy, providing an indicator of how much the estimated values deviate from the observed values. The RMSE vector is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i - \hat{u}_i)^2 + (v_i - \hat{v}_i)^2} \tag{2}$$

where:

- u_i, v_i are the actual wind velocity components at station i,
- $\hat{u}_i, \hat{v}_i$ are the interpolated wind velocity components,
- n is the total number of unknown points being evaluated.

Mean Absolute Error (MAE) To further evaluate directional accuracy, we calculate the Mean Absolute Error (MAE) for both the u (zonal) and v (meridional) wind components:

$$MAE_u = \frac{1}{n}\sum_{i=1}^{n} |u_i - \hat{u}_i| \tag{3}$$

$$MAE_v = \frac{1}{n}\sum_{i=1}^{n} |v_i - \hat{v}_i| \tag{4}$$

MAE provides a direct measure of how much the interpolated wind speed deviates from the actual recorded values, with lower values indicating better performance.

4. Results and Discussion

The performance of the interpolation methods was evaluated by comparing the interpolated wind speed and direction values with actual ground truth data from the designated validation stations. The primary error metric used for assessment was the RMSE vector, calculated for each interpolation method across different locations and wind conditions.

The RMSE vector distribution for each interpolation method is shown in Figure 4. The results indicate that **Ordinary Kriging** consistently produced the lowest interpolation error among all methods. This can be attributed to its ability to account for spatial autocorrelation while incorporating a large number of nearby weather stations, thereby enhancing local interpolation accuracy.

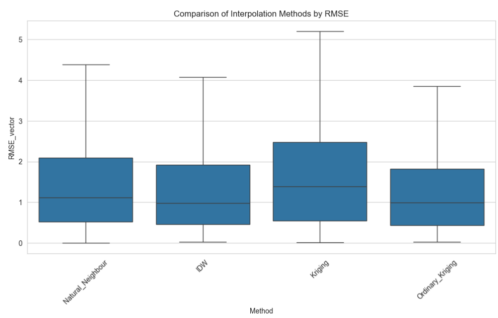

Figure 4. RMSE vector distribution by interpolation method.

It is evident that methods relying solely on distance-based weighting, such as IDW and Natural Neighbors, exhibited higher interpolation errors. The error values for different methods range up to approximately 5 m/s, emphasizing the importance of choosing an appropriate interpolation technique based on terrain complexity and weather station density.

4.1 Performance Across Different Locations

To further investigate the spatial variations in interpolation accuracy, RMSE values were analyzed for different station locations (Figure 5). The results highlight that interpolation accuracy varies significantly depending on the terrain and surrounding weather station density.

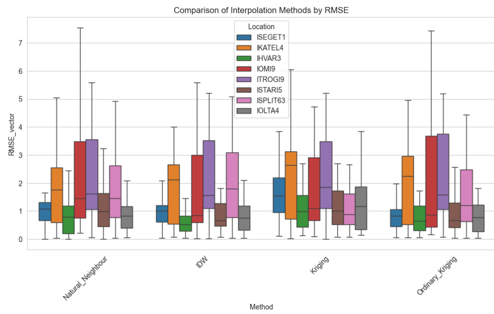

Figure 5. RMSE error by location across all methods.

The most challenging interpolation scenario was observed at the IOMI9 station, which is positioned inside a river canyon. This location exhibited the highest RMSE errors across all methods, despite having two nearby weather stations for reference. This shows that proximity alone is not a sufficient indicator of interpolation accuracy in complex topographical environments. The significant variation in wind speed and direction within the canyon, influenced by sudden gusts and turbulence, makes it inherently difficult to interpolate accurately.

These findings underscore that wind behavior in enclosed or obstructed terrains, such as canyons, is highly unpredictable. Even with dense observational data, standard interpolation methods struggle to capture the abrupt changes in wind dynamics within such environments.

4.2 Influence of Wind Type on Interpolation Accuracy

Further analysis was conducted to assess how different wind types impact interpolation accuracy. As shown in Figure 6, Bura produced the highest RMSE vector errors across all interpolation methods. This result aligns with expectations, as Bura is characterized by strong, turbulent gusts and rapid fluctuations in wind speed and direction, making it difficult to interpolate accurately.

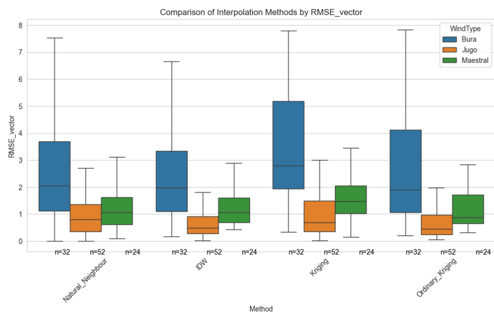

Figure 6. RMSE vector distribution by wind type.

In contrast, Jugo and Maestral exhibited significantly lower RMSE values, as these wind types are known for their steady and more predictable behavior. When analyzing the error distribution further, it is evident that RMSE values for Bura wind reach up to 8 m/s across all interpolation methods, with no single method significantly outperforming the others. The chaotic and gusty nature of Bura results in interpolation errors that remain relatively high across different techniques. For Jugo and Maestral RMSE values remain below 3 m/s, with Ordinary Kriging consistently achieving the best results. The smoother, more uniform wind patterns of these wind types contribute to improved interpolation accuracy.

4.3 Error Analysis by U and V Components

To further investigate the interpolation performance, the Mean Absolute Error (MAE) was analyzed separately for the two wind vector components: U (zonal) and V (meridional). Figures 7 and 8 illustrate the MAE distribution for each interpolation method across different locations.

Upon analyzing the results, it is evident that no clear trend emerges favoring a particular interpolation method for one component over the other. The interpolation errors for both the U and V components remain relatively consistent across methods, suggesting that none of the techniques inherently favor one wind component direction over the other.

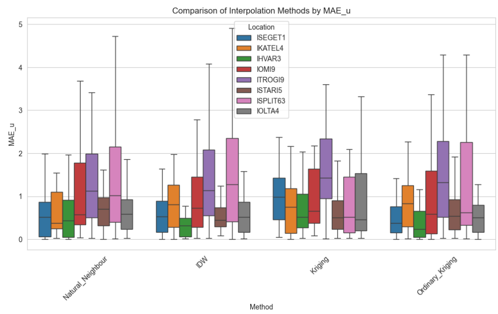

Figure 7. MAE for the U-component (zonal wind) across different interpolation methods.

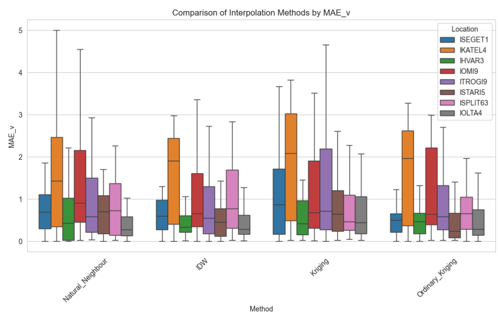

Figure 8. MAE for the V-component (meridional wind) across different interpolation methods.

This result was expected given that the interpolation methods applied do not treat wind components independently but rather interpolate the entire wind field as a vector quantity. Since wind is typically not constrained to blowing purely along the cardinal directions (north-south or east-west), interpolation methods are influenced by the combined effects of both components rather than treating them separately.

The wind patterns analyzed in this study primarily originate from mezoscale directional sectors such as southwest (SW), northwest (NW), and southeast (SE). As a result, both the U and V components are equally involved in defining the wind vector, leading to similar error magnitudes in both components. This indicates that interpolation accuracy is generally unaffected by whether the wind component is zonal (U) or meridional (V), as both contribute equally to the overall wind dynamics.

To gain deeper insight into interpolation accuracy, we analyze the Mean Absolute Error (MAE) separately for the U (zonal) and V (meridional) wind components, further segmented by wind type. This allows us to identify specific weather stations that contribute to higher interpolation errors.

The Maestral wind primarily blows from the northwest (NW), which suggests that errors in the U-component (zonal wind) should generally be smaller, as the dominant wind flow aligns with this axis. This expectation is largely confirmed in Figure 9, where seven weather stations exhibit low MAE values, remaining below 2 m/s. However, an exception is observed at the ITROGI9 station, which produces significantly higher interpolation errors—up to 5 m/s—despite being located in a dense measurement network surrounded by multiple weather stations. For the V-component (meridional wind), Figure 10 reveals that ITROGI9 continues to exhibit the highest error values. Additionally, the KASTEL4 station, positioned in a relatively remote beach location, shows a notable increase in error, reaching up to 3.5 m/s. In contrast, the remaining six weather stations maintain relatively low MAE values, with errors not exceeding 2 m/s in the V-component. These results suggest that errors in the meridional component are influenced by station positioning relative to the coastline and surrounding terrain.

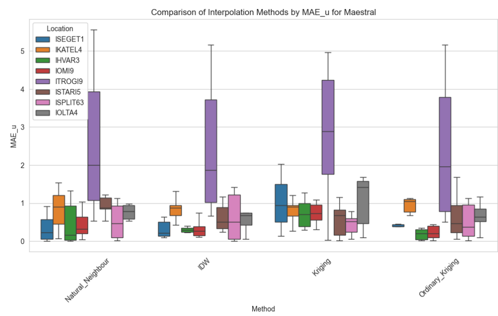

Figure 9. MAE for the U-component (zonal wind) for Maestral wind.

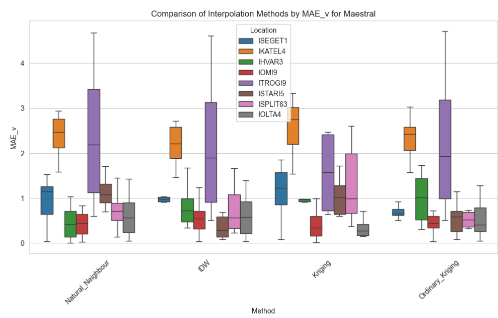

Figure 10. MAE for the V-component (meridional wind) for Maestral wind.

The Bura wind primarily blows from the northeast (NE) and is characterized by strong, turbulent gusts. Given its highly variable nature, interpolation errors in the U and V components are expected to be similar. This expectation is supported by Figures 11 and 12, where error distributions across components show comparable magnitudes. The highest MAE values occur at a weather station positioned inside a canyon, confirming that enclosed terrains significantly disrupt wind interpolation accuracy. The steep and narrow topography of canyons causes abrupt wind accelerations and directional shifts, leading to substantial interpolation errors. Conversely, the station IOLTA4, which is situated in a highly sheltered location, records the lowest MAE values. Its position effectively shields it from direct Bura exposure, reducing turbulence effects and leading to significantly improved interpolation accuracy.

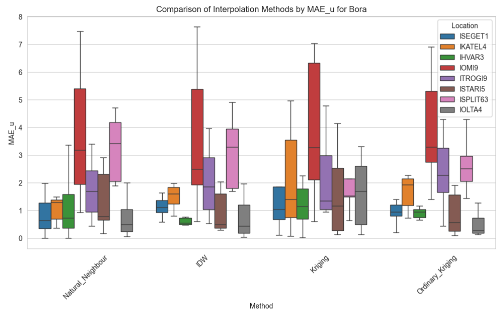

Figure 11. MAE for the U-component (zonal wind) for Bura wind.

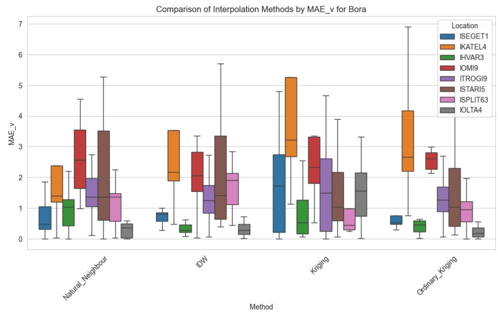

Figure 12. MAE for the V-component (meridional wind) for Bura wind.

Overall, the analysis reveals that interpolation errors for Maestral wind are generally lower, particularly in the U-component, except at the ITROGI9 station, which shows significant discrepancies despite being in a high-density measurement area. For the V-component of Maestral, KASTEL4, located near the coastline, exhibits increased error due to its relatively isolated positioning. In the case of Bura wind, interpolation errors remain high across both components, particularly in enclosed terrains such as canyons, where wind turbulence is most severe. On the other hand, sheltered locations, such as IOLTA4, experience significantly lower interpolation errors due to their protection from direct wind exposure. These findings emphasize the critical role of terrain complexity and station placement in determining interpolation accuracy, particularly for highly variable wind patterns such as Bura.

4.4 Interpolating Across the Whole Map

To extend the analysis beyond specific validation stations, we apply interpolation techniques to estimate wind conditions across the entire study region. Given that previous analyses have shown Bura to be the most unpredictable wind type, producing the highest interpolation errors, we focus on interpolating Bura wind conditions across the whole map. The interpolation was performed over a bounding box covering the Split-Dalmatia County, with grid points spaced every 100 meters in both latitude and longitude directions.

Figures 13 through 16 present the spatial distribution of interpolated wind fields using four different methods: Kriging, Ordinary Kriging, Inverse Distance Weighting (IDW), and Natural Neighbors. Each method provides a distinct perspective on how wind speed and direction are estimated across heterogeneous terrain.

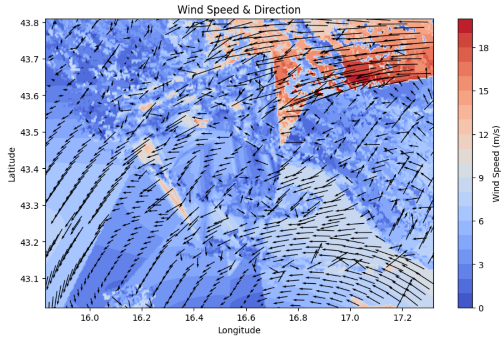

Figure 13. Kriging interpolation of Bura wind conditions across the study area.

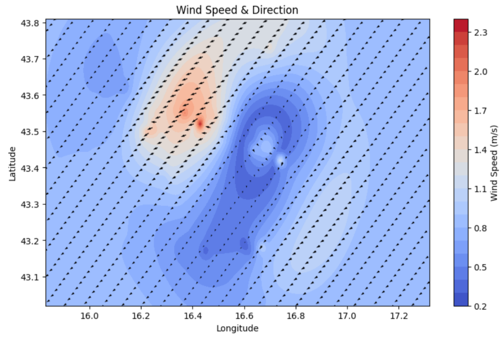

Figure 14. Ordinary Kriging interpolation of Bura wind conditions across the study area.

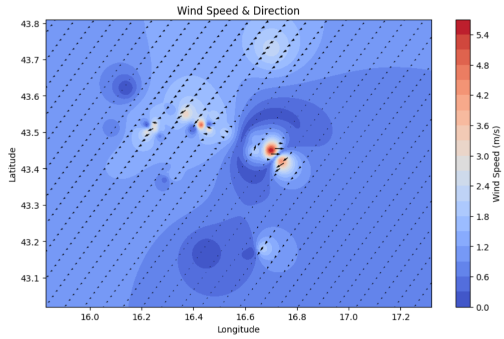

Figure 15. IDW interpolation of Bura wind conditions across the study area.

4.4.1 Comparing Interpolation Methods Across the Map

Unlike other interpolation methods that rely solely on meteorological data from weather stations, Kriging offers a more sophisticated approach by incorporating spatial correlation and adjusting the variogram to account for environmental factors. This allows Kriging to provide a more accurate estimation of wind direction, particularly in terrains where wind behavior is strongly influenced by surface roughness and landform boundaries.

As shown in Figure 13, Kriging interpolation reveals distinctly clustered wind directions that align with major landforms such as islands, river boundaries, and elevated terrain. These wind

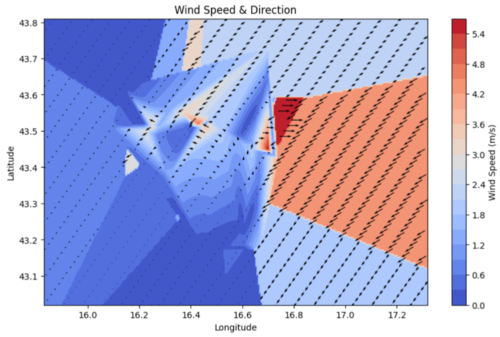

Figure 16. Natural Neighbor interpolation of Bura wind conditions across the study area.

patterns suggest that Kriging effectively captures the natural flow of wind as shaped by geographical features, reinforcing its suitability for wind field interpolation in heterogeneous environments.

In contrast, deterministic methods such as IDW (Figure 15) and Natural Neighbors (Figure 16) produce interpolation results that are more localized and less reflective of large-scale terrain influences. IDW, for example, assumes that nearby points have a stronger influence on interpolation but does not account for spatial autocorrelation, leading to less accurate wind predictions in complex topography. Similarly, the Natural Neighbor method, while effective in some cases, is limited by its reliance on immediate neighboring points, making it less adaptable to varying wind dynamics.

4.5 Key Findings and Implications

The analysis reveals that Ordinary Kriging outperforms other methods, especially in areas with dense weather stations, due to its ability to account for spatial autocorrelation. However, interpolation accuracy decreases in complex terrains, like canyons, where rapid wind fluctuations and turbulence create uncertainty.

Wind type significantly impacts performance: predictable winds such as Jugo and Maestral allow for more reliable interpolation, while turbulent winds like Bura cause larger errors. The chaotic nature of Bura makes it difficult for traditional methods to capture its variability. Kriging is especially effective in regions influenced by topography, like coastal zones and valleys, providing a more meaningful interpolation for wind energy assessments and meteorological modeling.

No method shows a clear advantage for U or V components, as both contribute equally to accuracy. Wind patterns in the region, mainly diagonal directions, explain the balanced influence of both components on accuracy. Error magnitudes for U and V remain similar, highlighting the influence of wind variability and terrain complexity over individual components.

These findings stress the need to tailor methods to terrain, wind conditions, and station density. While Ordinary Kriging is the most reliable, no method fully captures extreme wind variability, particularly in high-turbulence scenarios like Bura. Future work should explore machine learning or hybrid approaches, as well as incorporating dynamic meteorological parameters to improve accuracy in complex environments

5. Conclusion

This study evaluated the accuracy of four spatial interpolation methods—Kriging, Ordinary Kriging, Inverse Distance Weighting (IDW), and Natural Neighbors—for estimating wind speed and direction in Split-Dalmatia County, Croatia. The region's diverse geography, including coastal areas, islands, urban centers, and mountainous terrains, poses challenges for wind interpolation due to varying topographical influences and wind dynamics.

Results show that interpolation accuracy depends not only on the choice of method but also on the spatial distribution of weather stations, terrain complexity, and prevailing wind conditions. Ordinary Kriging proved to be the most reliable method amog evaluated, particularly in regions with a higher station density, but still struggled in areas with extreme topographical influences and highly turbulent wind patterns such as those produced by Bura winf.

Future research should explore hybrid modeling approaches, integrating machine learning techniques or weather prediction models to enhance interpolation accuracy, particularly in regions affected by extreme wind variability. Additionally, incorporating dynamic meteorological parameters such as pressure gradients, real-time turbulence indices, and high-resolution topographical modeling could further refine interpolation techniques.

All code, data, and preprocessing scripts used in this research are available at: `https://github.com/mradic01/FOSS4G`.

References

Journel, A. G., Huijbregts, C. J., 1978. *Mining Geostatistics*. Academic Press.

Keskin, M., Ozdogu, K., 2011. Comparison of interpolation methods for meteorological data. *Bachelor Thesis, Istanbul Technical University, Istanbul, Turkey*.

Krige, D. G., 1951. A Statistical Approach to Some Basic Mine Valuation Problems on the Witwatersrand. *Journal of the Chemical, Metallurgical and Mining Society of South Africa*, 52, 119-139.

Matheron, G., 1963. Principles of Geostatistics. *Economic Geology*, 58(8), 1246-1266.

Nynke Hofstra, Malcolm Haylock, M. N. C. F., 2008. Comparison of Six Methods for the Interpolation of Daily European Climate Data. *Journal of Geophysical Research*, 113. https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2008JD010100.

Pratik Nag, Ying Sun, B. J. R., 2023. Bivariate DeepKriging for Large-scale Spatial Interpolation of Wind Fields. *ArXiv*. https://arxiv.org/abs/2307.08038.

Shepard, D., 1968. A two-dimensional interpolation function for irregularly-spaced data. *Proceedings of the 23rd ACM National Conference*, 517–524.

Sibson, R., 1981. A Brief Description of Natural Neighbor Interpolation. *Interpreting Multivariate Data*, 21-36.

Weather Underground, n.d. https://www.wunderground.com.